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Research Paper

Hybrid Deep and Ensemble Learning for Transportation Mode Detection using Sliding-Window Sensor Data

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Abstract

Transportation mode detection is an essential component of Human Activity Recognition (HAR) systems, supporting applications such as smart mobility, personalized navigation, and urban planning. Traditionally, these systems relied on manual observation, surveys, or simple threshold-based methods using smartphone or wearable sensors. Such approaches were often limited in accuracy, required extensive human intervention, and could not capture complex, non-linear patterns in multi-sensor data. The proposed system, MetaFuseNet, is a hybrid deep and ensemble learning framework designed for accurate detection of transportation modes including walking, still, car, bus, and train using sliding-window sensor data. MetaFuseNet integrates a Deep Neural Network (DNN) to model temporal and non-linear relationships, a Random Forest Classifier (RFC) for robust feature-based decision-making, and a Logistic Regression (LR) meta-model to combine predictions from the base models for improved performance. Additionally, traditional classifiers such as K-Nearest Neighbors (KNN) and Logistic Regression (LR) are evaluated for benchmarking. The system is implemented in Python using TensorFlow, Keras for deep learning and scikit-learn for classical machine learning. A Flask-based web interface enables users to upload sensor data files and obtain real-time predictions using the pre-trained models, without requiring retraining. This research delivers a complete end-to-end pipeline for transportation mode prediction, combining advanced deep learning, ensemble learning, and meta-model stacking techniques. By providing automated, accurate, and efficient activity recognition, the system demonstrates a practical solution for real-time transportation monitoring and intelligent mobility applications.

Keywords: Transportation Mode Detection, Human Activity Recognition (HAR), Deep Neural Networks (DNN), Ensemble Learning, Meta-Learning, MetaFuseNet

1. Introduction

In earlier decades, traditional mechanical vehicles enabled faster and more efficient transportation. However, the rise of smart cities has transformed urban infrastructure, introducing interconnected systems that collect and share data to support intelligent operational decisions. Alongside this development, a new generation of vehicles Connected and Autonomous Vehicles (CAVs) has emerged, offering enhanced comfort and advanced driving capabilities. These vehicles rely on Vehicular Ad Hoc Networks (VANETs) to make optimal driving decisions by analysing onboard sensor data and integrating information exchanged wirelessly with other connected vehicles as shown in Figure. 1. Despite these benefits, the dependence of CAVs on continuous communication exposes them to significant cybersecurity risks. Vulnerabilities in communication interfaces can be exploited

to compromise control systems or manipulate sensor data, potentially causing accidents or endangering passengers. Consequently, implementing robust cybersecurity measures is critical to protect these vehicular networks and ensure safe and reliable operation. Modern vehicles rely on Electronic Control Units (ECUs), sensors, and communication protocols such as FlexRay, LIN, and the widely used Controller Area Network (CAN) bus.

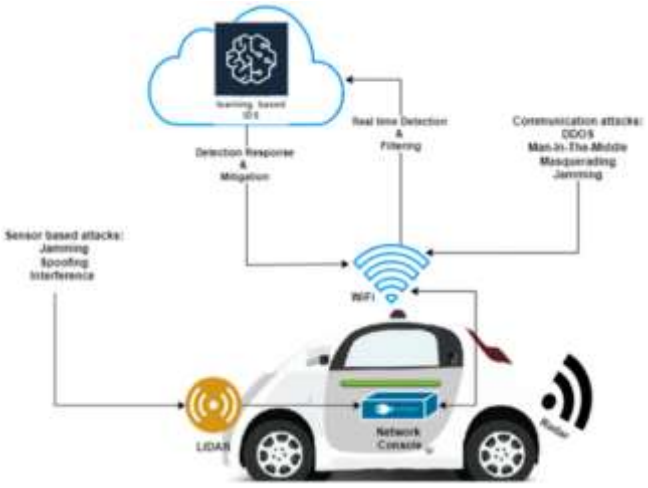

Figure. 1: Intrusion detection system for vehicles.

While CAN is favoured for its real-time responsiveness and cost-effectiveness, it lacks native security features such as confidentiality, authenticity, and access control. This absence makes vehicles increasingly vulnerable to intrusions at both the in-vehicle and network communication levels. To counter these threats, two main defence mechanisms are commonly explored: cryptographic techniques and intrusion detection systems (IDS). While cryptography offers strong protection, it imposes high computational overhead. IDS, on the other hand, provide lightweight, real-time monitoring and early detection of suspicious activity. However, traditional IDS approaches (e.g., signature-based methods) are limited in detecting novel and evolving attacks.

2. Literature Survey

Further advances using deep residual and recurrent network architectures confirm that accurate temporal alignment and structured feature fusion across multiple sensor streams are essential for robust and scalable transportation pattern recognition [1]. Beyond algorithmic performance, the importance of structured data handling, transparency, and trust in IoT-enabled sensing environments has been emphasized. Frameworks addressing data observability and accountability demonstrate that clearly defined data pipelines and annotation workflows are essential when managing heterogeneous sensor data at scale [2]. The importance of synchronized multi-sensory datasets is further demonstrated through large-scale vehicular and mobility datasets. Transportation datasets built from multimodal smartphone sensors illustrate how high-quality sensor alignment supports generalizable transportation mode recognition across diverse usage scenarios [3].

Shivanna et al. [4] review IoT-connected traffic sensor systems and highlight how accurate sensor data annotation supports edge intelligence, object tracking, and real-time deployment in smart-city infrastructures. Synchronized annotation tools are identified as essential enablers of such deployments. In vehicular cyber-physical systems, time-synchronized datasets combining video, inertial, GPS, and magnetic sensors enable reliable benchmarking of sensor-fusion and perception algorithms under real-world traffic conditions [5]. Despite the availability of synchronized datasets, annotation remains a major practical bottleneck. Smart annotation tools that integrate synchronized

sensor streams with human-in-the-loop support have been shown to significantly reduce manual labelling effort while improving temporal consistency and label quality [6]. Complementary intelligent dataset construction pipelines further demonstrate that tool-assisted approaches improve noise filtering, scalability, and downstream machine-learning performance [7]. Advanced vehicle detection methods based on cross-scale feature fusion further demonstrate that balanced and accurately annotated datasets across different object scales are essential for achieving consistent detection accuracy in complex traffic scenes [8].

Dataset quality has been repeatedly identified as a dominant factor influencing perception system performance. Comprehensive reviews of vehicle detection under adverse environmental conditions highlight that annotation accuracy, dataset diversity, and sensing quality critically affect detection robustness in real-world deployments [9]. Beyond conventional visual sensing, alternative dataset modalities also play an increasingly important role. Large-scale acoustic datasets for emergency vehicle and traffic sound detection demonstrate that carefully labelled sensor data enable highly accurate detection systems for intelligent transportation and public safety applications [10]. Event-based and hybrid vision datasets providing synchronized event streams and frame-based imagery with precise ground-truth annotations further illustrate the growing demand for high-quality, temporally aligned multimodal datasets in automotive detection and tracking tasks [11]. Our dataset tool similarly supports metadata-driven labelling to facilitate algorithmic vehicle-type classification. Taken together, these works illustrate the demand for specialized annotation tools tailored to MEMS-based sensor systems in traffic environments. The following sections describe the system architecture, implementation details, and practical validation through real-world use cases.

Liang et al. [12] demonstrated that high-speed autonomous vehicles can significantly improve their cruising performance when supported by an integrated deep reinforcement learning framework. Their study highlights that such learning-based systems depend strongly on high-quality training data to handle fast-changing traffic situations safely and efficiently. Chen et al. [13] analysed large-scale vehicle trajectory data to investigate differences in lane-changing behaviour on highways. Their results show that detailed, precisely labelled movement data are essential for understanding how drivers behave in real traffic and for developing more realistic traffic behaviour models. Zhai et al. [14] examined how cyber-attacks and external disturbances can influence traffic stability by using a multi-phase hydrodynamic traffic model with a self-stabilizing control protocol. Their findings emphasize the importance of accurate traffic data for designing robust control strategies that can maintain stability even under abnormal or hostile conditions. This includes traditional human-powered options (e.g., bicycles, kick scooters) and their electric counterparts. Electrically powered micro-mobility modes e-scooters and e-bikes are rapidly gaining popularity, both in private ownership and through shared systems [15, 16].

3. Proposed Methodology

The proposed system focuses on automatic transportation mode detection using multi-sensor data collected from smartphones and wearable devices. Unlike traditional approaches, this project leverages a hybrid model combining DNN and RF with a stacking meta-model to achieve high accuracy in predicting user activities such as walking, driving, traveling by bus or train, or being still as shown in figure 2. Sensor data is first segmented using a sliding-window approach, allowing the extraction of temporal and statistical features over fixed intervals. A DNN captures complex temporal dependencies in the data, while a RF classifier handles feature robustness and reduces the impact of noise. The predictions from both models are then combined using a LR meta-model, which acts as a fusion layer to improve overall performance. The system also integrates a Flask-based web

application that allows users to upload CSV files containing sensor data. The hybrid model then predicts the transportation mode in real-time and presents results through a user-friendly interface. This end-to-end system provides scalable, accurate, and real-time transportation mode detection, which can be deployed for urban mobility analysis, fitness tracking, and smart city applications.

Data Acquisition: Sensor data such as accelerometer, gyroscope, and GPS readings is collected from smartphones or wearable devices. The data is segmented into fixed-length sliding windows to capture temporal movement patterns. Each window represents a short period, enabling accurate detection of transitions between transportation modes.

Data Preprocessing: Raw sensor data is cleaned to remove missing values and duplicates. Categorical features are encoded using LE, and numerical features are standardized for uniformity. Preprocessing ensures models can learn patterns efficiently without being affected by scale differences or inconsistent data.

Model Training: Multiple models are trained on the pre-processed data to capture different aspects of movement. DNN learns complex non-linear and temporal relationships, while RFC leverages feature-based decision-making. Traditional models like KNN and LR are also trained for benchmarking.

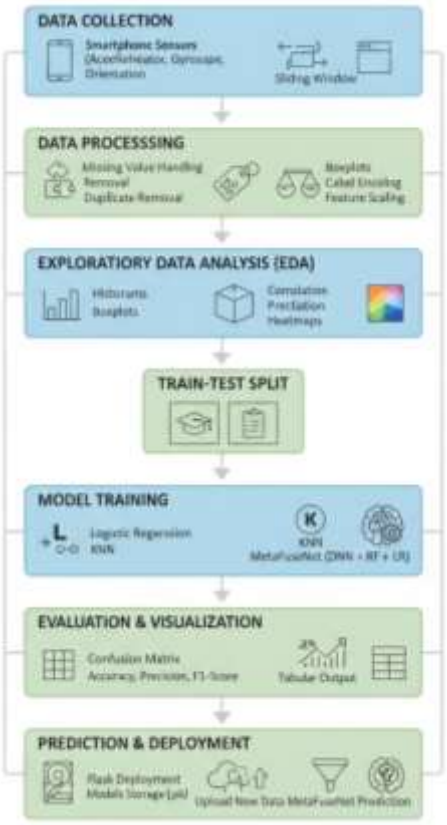

Figure. 2: Proposed System Architecture.

Hybrid Stacking with MetaFuseNet: Predictions from DNN and RFC are combined using LR meta-model, forming the hybrid MetaFuseNet framework. This stacking approach enhances overall accuracy, robustness, and reliability of transportation mode detection.

Real-Time Prediction Interface: A Flask-based interface allows users to upload new sensor data files and receive predictions instantly. The system processes the data, applies the trained

MetaFuseNet, and outputs the predicted transportation mode in real time, making it practical for users and urban applications.

Evaluation: The system is evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. Confusion matrices and ROC curves are generated to assess per-class performance, ensuring the system is reliable and effective across all transportation modes.

4. Result Description

The results analysis section evaluates the performance and effectiveness of the proposed system in achieving accurate and reliable outcomes. It focuses on assessing the model using various evaluation metrics such as accuracy, precision, recall, and F1-score to ensure comprehensive performance measurement. The analysis also compares the proposed approach with existing methods to highlight improvements and advantages. Graphical representations and visualizations are utilized to clearly interpret the results and identify patterns or trends. Additionally, the robustness and generalization capability of the model are examined using test datasets. This section provides critical insights into the strengths and limitations of the system, ensuring its suitability for real-world applications.

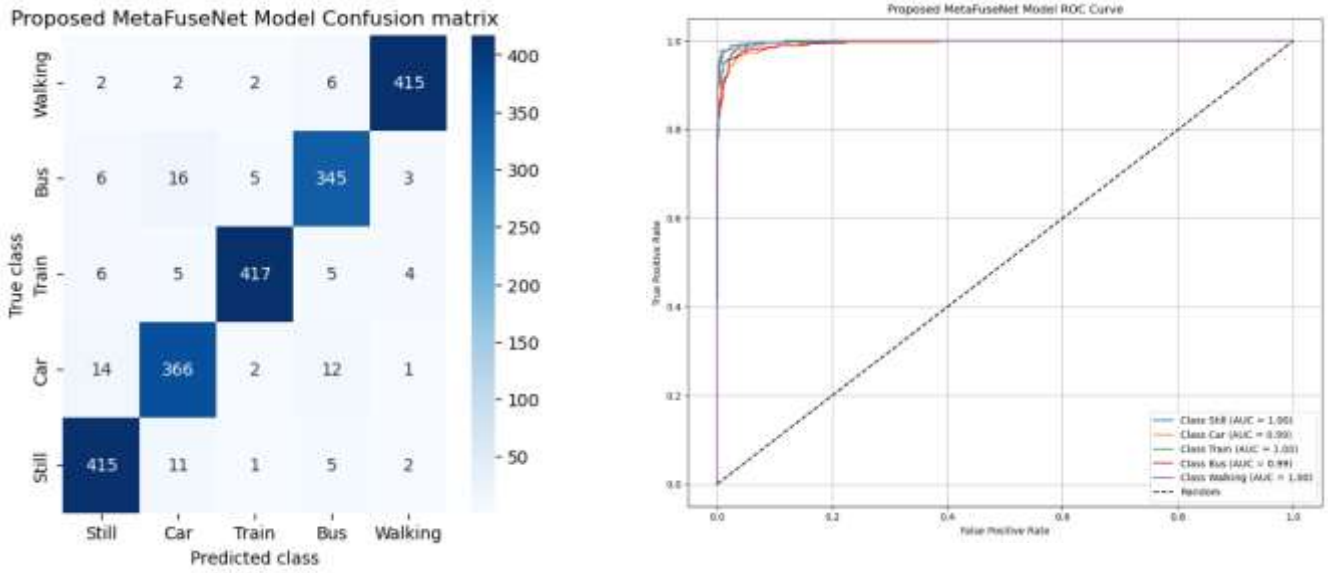

Figure. 3: Obtained confusion matrix and ROC curve from MetaFuseNet Model

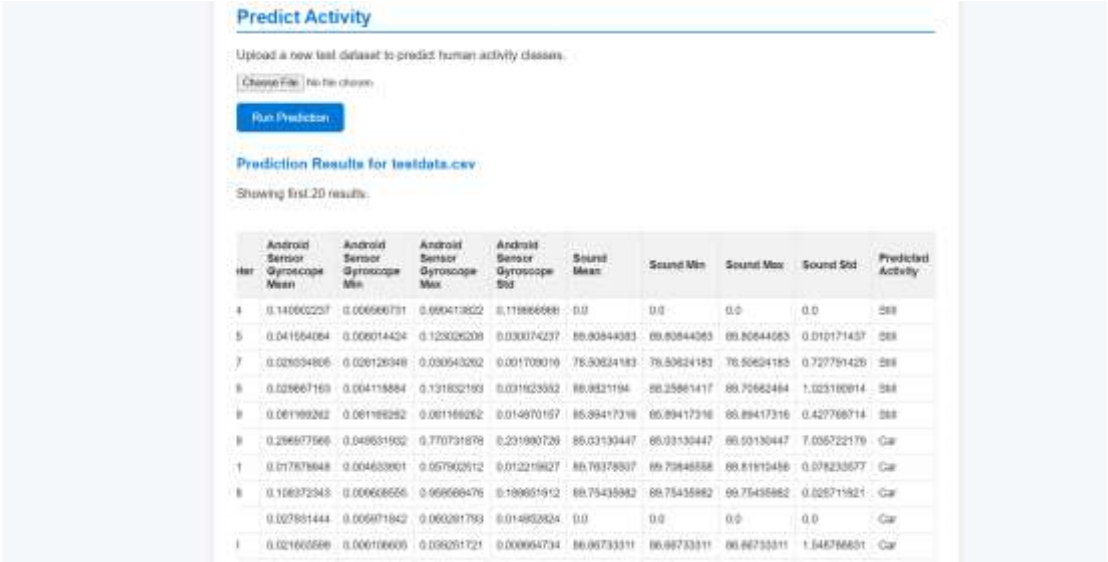
Predict Activity
Upload a new test dataset to predict human activity classes.
Run Prediction
Prediction Results for testdata.csv
Showing first 20 results.

Figure. 4: Predictions screen

Figure 3 illustrates the performance evaluation of the proposed MetaFuseNet model through a confusion matrix and ROC curve analysis, highlighting its classification effectiveness across five activity classes: Still, Car, Train, Bus, and Walking. The confusion matrix demonstrates strong diagonal dominance, indicating high true positive rates, with particularly accurate predictions observed for Still, Train, and Walking classes. Minor misclassifications are present but remain relatively low, suggesting robust inter-class separability and reliable model generalization. The ROC curves further depict the discriminative capability of the model, with all classes achieving near-perfect Area Under the Curve (AUC) values close to 1.00. The curves remain consistently close to the top-left corner, signifying high sensitivity and specificity across varying thresholds. Additionally, the minimal gap between different class curves indicates balanced performance without significant bias toward any single class.

Figure 4 illustrates the prediction interface of the proposed MetaFuseNet system, designed for automated human activity recognition using uploaded test datasets. The figure depicts the workflow where users input a dataset file and initiate the prediction process, resulting in classified activity outputs. The tabular results section presents multiple sensor-derived features, including gyroscope-based statistical measures and sound-related attributes, which are utilized as inputs to the trained model. Each row corresponds to an instance from the dataset, with computed feature values mapped to a predicted activity label such as Still or Car. The structured representation of predictions demonstrates the model's capability to process real-time or batch data efficiently and generate accurate classifications. Furthermore, the presence of diverse feature columns highlights the multimodal data fusion approach employed by the model for improved recognition performance.

Table. 1: Overall Comparison table

MODEL	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR	55.6	56.0	55.3	55.3
KNN	66.0	66.7	65.4	65.7
MetaFuseNet	94.6	94.5	94.5	94.5

The table 1 presents a comparative performance analysis of three models used for transportation mode detection LR, KNN, and the proposed MetaFuseNet hybrid model. The LR model achieved an accuracy of 55.6%, with precision, recall, and F1-score values around 55–56%, reflecting its limited ability to capture complex patterns in sensor data. The KNN model improved performance, achieving 66% accuracy and slightly higher precision and recall, demonstrating better handling of non-linear relationships. In contrast, the MetaFuseNet model significantly outperformed both individual models, achieving an accuracy of 94.6% along with precision, recall, and F1-score values of 94.5%, indicating its superior capability to integrate deep learning and ensemble techniques for precise transportation mode classification. This comparison highlights the effectiveness of the hybrid approach in capturing complex sensor patterns and providing robust predictions.

5. Conclusion

The research successfully demonstrates the integration of deep learning and ensemble machine learning techniques to accurately classify user transportation modes from multi-sensor smartphone data. The system preprocesses raw accelerometer, gyroscope, and orientation sensor readings, performs exploratory data analysis, and applies feature scaling and label encoding to prepare the data for modelling. Three models were implemented and evaluated LR, KNN, and the proposed

MetaFuseNet hybrid model. Comparative analysis shows that the MetaFuseNet model achieves superior performance with 94.6% accuracy, significantly outperforming the traditional LR and KNN models. The hybrid approach effectively combines the strengths of DNN and RF classifiers through stacking with LR, capturing complex sensor patterns that individual models cannot detect. Additionally, the implementation of a Flask-based web application allows users to upload datasets, perform real-time predictions, and visualize results seamlessly, demonstrating the practical applicability of the system.

References

[1] Explainable AI Framework for Policy-Compliant Anomaly Detection in Data Pipelines. (2025). Inaternational Journal of Communication Networks and Information Security, 16(4). https://doi.org/10.48047/ijcnis.16.4.2111

[2] Madaan, A.; Wang, X.; Hall, W.; Tiropanis, T. Observing Data in IoT Worlds: What and How to Observe? In Living in the Internet of Things: Cybersecurity of the IoT; IET: London, UK; pp. 1–7.

[3] Gaddam, S. From Fixed Specifications to Self-Adapting Systems: A Machine Learning Perspective on Software Engineering.

[4] S. M. K. P. (2025). Cryptography in iOS: A Study of Secure Data Storage and Communication Techniques. International Journal on Science and Technology, 16(1). https://doi.org/10.71097/ijsat.v16.i1.1403

[5] Alam, K.M.; Hariz, M.B.; Hosseinioun, S.V.; Saini, M.; El Saddik, A. MUDVA: A Multi-Sensory Dataset for Vehicular Cyber-Physical System Applications. In Proceedings of the 2016 IEEE 18th International Workshop on Multimedia Signal Processing (MMSP), Montreal, QC, Canada, 21–23 September; pp. 1–6.

[6] Reddy, S. K. R. (2024). Designing Blockchain Architecture to Transform Loyalty Rewards into Cryptocurrency Investments.

[7] Poojari, R. (2025). A Comparative Analysis of Fine-Tuning Versus Retrieval-Augmented Approaches for Enhancing Healthcare-Centric Large Language Models.

[8] Kalae, U. K. (2021). Enhancing data analytics and reporting efficiency using Power BI and SQL in cloud computing environments. Journal of Computational Analysis and Applications, 29(6), 2021. https://doi.org/10.48047/jocaaa.2021.29.06.48

[9] Vasagam, M., Kumar, A., & Garg, A. (2026). Learning Execution Plan Embeddings for Multi-Dimensional Query Resource Prediction. IEEE Access.

[10] Shams, M.Y.; Abd El-Hafeez, T.; Hassan, E. Acoustic Data Detection in Large-Scale Emergency Vehicle Sirens and Road Noise Dataset. Expert Syst. Appl. 2024, 249, 123608.

[11] Patyrykin, K., & Vasyukova, L. (2025). Environmental Accountability or Symbolic Compliance? A Critical Review of ESG Ratings, Greenwashing, and Indirect Emissions in the Global Insurance Sector. International Journal of Energy Economics and Policy, 15(6), 917–925. https://doi.org/10.32479/ijeep.22770

[12] Santthosh Saai Reddy Purmani. (2026). Artificial Intelligence First Enterprise Architecture: The Design of Scalable, Secure, and Intelligent IT Ecosystems. American

Journal of AI Cyber Computing Management, 6(1(2)), 1–8. https://doi.org/10.64751/ajaccm.2026.v6.n1(2).pp1-8

[13] Chen, S.; Piao, L.; Zang, X.; Luo, Q.; Li, J.; Yang, J.; Rong, J. Analyzing differences of highway lane-changing behavior using vehicle trajectory data. Phys. A Stat. Mech. Its Appl. 2023, 624, 128980.

[14] Zhai, C.; Wu, W.; Xiao, Y.; Zhang, J.; Zhai, M. Jam traffic pattern of a multi-phase lattice hydrodynamic model integrating a continuous self-stabilizing control protocol to boycott the malicious cyber-attacks. Chaos Solitons Fractals 2025, 197, 116531.

[15] Schumann, H.H.; Haitao, H.; Quddus, M. Passively generated big data for micro-mobility: State-of-the-art and future research directions. Transp. Res. Part D Transp. Environ. 2023, 121, 103795.

[16] Kaya, Ö. Designing green and safe micro mobility routes: An advanced geo-analytic decision system-based approach to sustainable urban infrastructure. Eng. Sci. Technol. Int. J. 2025, 64, 102027.